Detection of Malignancy in Mammogram by CAD Tools – A Survey

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ABSTRACT

Breast cancer is one of the most common and life threatening disease among women. Women over the age of 50 get the high risk of breast cancer and it may occur for even at the age of 30 [1]. Early detection of breast cancer is very important in cancer treatment. It increases the survival rate and gives more options for treatment. Mammogram plays a vital role on breast cancer diagnosis. Radiologist identifies malignant tissue visually from mammographic images. Computer aided diagnostic (CAD) tools helps radiologist, for an enhanced identification of malignancy in mammogram. The intention of this survey paper is to endow with an overview of recent advances in the development of CAD systems and related techniques.

KEYWORDS

Breast cancer, lesion, mammography, masses, and microcalcification.

I. INTRODUCTION

Cancer is a disease which is an abnormal growth of the cell in the body which may spread and grow to the other parts of the body whereas benign tumour doesn't spread. Breast cancer occurs due to damage in cell's DNA [2] and reason for such damage is not identified. As the age of the women increases risk factor of breast cancer also increases. Overall 14% of all cancers in women are breast cancer [3]. For every 28 women one woman is identified with breast cancer [3]. Oncologist says early detection of cancer is curable whereas cancers detected in later stages are treatable. Uneven growth of cells and rapid division of cells in breast leads to masses, lumps, microcalcifications, architectural disorder and asymmetry in breast. Ductal carcinoma in situ (DCIS), also called as intraductal carcinoma, is a pre-cancerous or non-insidious cancerous lesion of the breast [4]. DCIS is classified as pre stage cancer. Invasive carcinoma is the most common form of invasive breast cancer. It accounts for 55% of breast cancer incidence upon diagnosis [5]. It is usually a mass with fine spikes radiating from the edges.

II. MAMMOGRAM

One of the major screening techniques for breast cancer is mammography. It is X-ray imaging of breast. It is widely accepted imaging technique for breast cancer detection [6]. Mammogram consists of four images craniocaudal (CC) which is top view and mediolateral oblique (MLO) which is side view of both breasts. Medial tissue is visualized clearly in CC projection when compared to MLO. Different mammographic images are available for researchers as a database in (DDSM) Digital Database for Screening Mammography, (MIAS) Mammographic Image Analysis Society, Hologic digital mammographic system, GE senographe system and Siemens mammomat inspiration system.

Noise in mammogram can occur due to image acquisition and breast anatomy. Image acquisition gives (i) quantum noise occur by photon fluctuation, (ii) electrical noise is of data flow in circuits & (iii) scattering noise due to interaction of X-ray with object usually blur effect. Breast anatomy noise occurs due to projection of 3D anatomical breast structure super imposed in 2D image.

Unfortunately mammography also has difficulty in reading results due to low contrast and involvement of human factor in the screening process. In the references shown that, radiologist has an error up to 30% on detection of cancer in mammogram. This error can be defined by various terms such as

Sensitivity, specificity and accuracy [7].

- ➢ Sensitivity measures how perfect the test detects disease is positive.
- ➢ Specificity is measure of patient can be ruled out who has no disease.
- ➢ Accuracy is measure of perfection in the diagnosis test.

True positive (TP)

Patient is having a disease and test also says disease exists, then it is called true positive.

True negative (TN)

Patient is having no disease and test also says disease doesn't exist, then it is called true negative.

False positive (FP)

Patient is having no disease and test says disease exists, then it is called false positive.

False negative (FN)

Patient is having a disease and test says disease doesn't exist, then it is called false negative.

Sensitivity or TPR (true positive rate) = $\frac{\text{TP}}{\text{TP + FN}} = \frac{\text{True positive appraisal}}{\text{All positive appraisal}}$

Specificity = $\frac{\text{TN}}{\text{TN + FP}} = \frac{\text{True negative appraisal}}{\text{All negative appraisal}}$

Accuracy = $\frac{\text{TN + TP}}{\text{N}} = \frac{\text{Correct appraisals}}{\text{All appraisals}}$

FPR (false positive rate) = $\frac{\text{FP}}{\text{TN + FP}}$ i-e FPR = 1-specificity

ROC curve

It is receiver operating characteristic graph which is plot of TPR and FPR. It is used for diagnosis studies.

FROC curve

It is free response receiver operating characteristic graph which is plot of sensitivity and FPI. It is used for detection studies.

FPI = $\frac{\text{Number of false positive marks}}{\text{Number of images}}$

III. COMPUTER-AIDED DETECTION & DIAGNOSIS OF BREAST CANCER

Computer aided detection (CAD) is a computerised image processing approach which acts as an aid or second opinion to radiologist to detect the presence of lesion in mammogram. CAD system consists of pre-processing, segmentation, feature extraction and classification.

A. Pre-Processing

Pre-processing is a process to improve contrast of mammograms by denoising and enhancement. A young woman who has dense breast tissue mammogram shows less contrast between glandular tissue which is normal and malignant tissue because X-ray has almost same attenuation between these two tissues. Several methods were proposed to denoising such as rescaling to equalise noise, Laplacian scale spaced noise equalization, threshold variance equalization and many [8]. Noise increases as image pixel intensity increases and they are dependent on each other [9]. Gaussian additive noise can be removed by semi blind noise reduction algorithm using steerable wavelet pyramid [10]. Adaptive statistical model to remove image noise by [11] uses wavelet coefficient with Gaussian variable. Bayesian probabilistic with markov random field model proposed by [12] to estimate original value from noise background. Microcalcification enhancement from noise by discrete wavelet transform proposed by [13] and continuous wavelet transform by [14].

B. Segmentation

Segmentation is a process to separate malignant tissue from breast fatty & fibro-glandular tissue. Fuzzy c-means with LDA classifier was proposed by [15] for segmentation based on breast density. Combination of adaptive thresholding with fuzzy logic by [16] gives increase in classification accuracy from 67.4% to 75%. Cumulus-like thresholding is an intensity threshold to segment fatty tissue and radio dense tissue by [17].

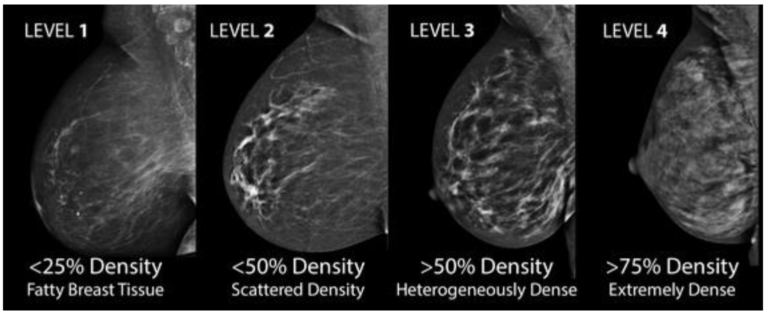
C. Feature extraction

Features of cancer cells are a distinctive attribute or character of malignant tissue. Breast cancer's two important features were researchers concentrating are Breast density and Patterns of the breast density. Breast density is used to illustrate the discrepancy in dense tissue on a mammographic image. In mammogram, breast region contains fatty tissue which looks darker and dense tissue looks brighter. Patterns of density play a key role in breast cancer risk. Two breasts mammogram can have alike percent of density, but the dense tissue is scattered in different patterns all over the breast.

Fatty breast tissue in mammogram is more translucent than in fibro-glandular breast tissue. Mammogram with fatty breast tissue, scattered density, heterogeneously distributed density and extremely dense breast are shown in figure 1.

Mammogram with various densities. [mammalive.net]

Fig. 1.



Atam P. Dhawan et al., [18] proposed computation of features by joining the pixel value of the similar character which results in (1) Number of malignant tissue location (2) average number of pixels per malignant tissue area (3) standard deviation of amount of pixels per malignant tissue (4) average gray level per malignant tissue (5) standard deviation of intensity of gray levels (6) average distance between malignant tissue (7) standard deviation of separation distances between malignant tissue (8) average separation distance between malignant tissue and center of mass (9) standard deviation of separation distances between malignant tissue and center of mass and (10) Potential energy of the arrangement using the product of the average gray level and the region as an indicator of mass.

D. Classification

After feature extraction from the data pattern, classification of normal, benign and malignant are developed using several approaches which depends on the features available. Choice of the classifier is a complicated task it depends on the probability of pattern belongs to a particular class. Reference [18] provides k-NN density estimator classifies microcalcification using feature vector. A hybrid classifier proposed by [19] has linear discriminant analysis (LDA) with adaptive resonance theory uses neural network scheme which is a supervised classifier. Support vector machine (SVM) with LDA was proposed by [20] to get better classification.

Liyang Wei et al.,[21] proposed support vector machine (SVM) based on the theory of structural risk minimization, kernel Fisher discriminant (KFD) based on the theory of projecting the data against a one-dimensional space, relevance vector machine (RVM) based on Bayesian estimation for regression and classification, feed forward neural network (FFNN) is a automated classifier for microcalcification and committee machines or methods works on the principle by combining output of group of learning machines with two strategies such as ensemble averaging and boosting these classifier's gives accuracy upto A_z 0.85 which is area under ROC curve.

IV. KEY TECHNIQUES FOR CAD SYSTEM

Many CAD techniques have been proposed by many researchers for detection of abnormalities in the breast mammogram. New algorithms were proposed for detection of masses, microcalcification, Architectural disorder and bilateral asymmetry were reported recently in the literature.

A. Methods for detection of Masses in Mammogram

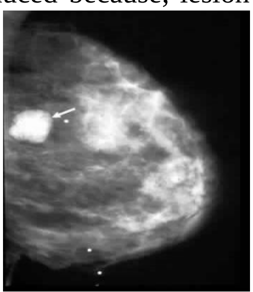
A mass is defined as a space which has lesion seen in many projections. Shape and margin are used to characterise a mass. In general, a regular shape mass is benign and irregular shape mass is malignant.

Diagnosis accuracy reduced due to non scalability of retrieval images in content based image retrieval technique for large database. To overcome this **Menglin Jiang et al.,** [22] proposed Scalable Image Retrieval technique Scale invariant feature transform (SIFT) were extracted from large database. Region of interest (ROI) were quantized and listed in Vocabulary tree. SIFT features were extracted from uncertain ROI and compared for the similarities in database. The ROIs of database which is similar to query ROI were used to find whether query has mass or normal. Retrieval precision is 88.4 % to find mass by tree feature method. Classification accuracy of 86.9% obtained for large dataset of 10553 sizes.

Mammogram with Mass [meddean.luc.edu]

Fig. 2.

Detection rate of masses gets reduced because, lesion with neighbouring shadows



and internal echo affect the detection. **Woo Kyung Moon et al.,** [23] proposed multi scale blob detection algorithm increases this rate. Mammography uses X-rays, which gives non distinguishable images between cyst filled with fluid and mass especially in dense tissue. ABUS uses ultrasound can overcome this difficulty and it gives nearly 200 3D images which helps for diagnosis in assist with mammography. Speckle noise reduction was performed by edge preventing smoothing filters and it retains edge information. Speckle noise was removed by sigma filter by retaining boundary information. Hessian analysis in Multi scale blob detection, was done to compute the three dimensional directions of its 2nd derivatives by convolving the ABUS image with derivatives of the Gaussian kernel. It enhances several geometrical shapes, as blobs, tubes, and plate- like structures. In ABUS images, small-scale blob detection segmented small lesion boundaries better compared to large scale detection, where the lesions were segmented into many fragmented regions. Large scale blob detection could segment the main part of a lesion with high internal echo, but the segmented result was coarser than that of small scale blob detection.

Due to the high sensitivity of the blobness measurement, many unwanted non tumors were also included with the tumor contender. If all were used in the process of tumor likelihoods, then it may take long time and also result in the poor performance of the CADe system due to high occurrence of false positives. To eliminate the False Positives this selection was processed. High blobness values of the candidate indicate that it was as same as a dark blob-like structure. Comparatively non tumors have lower blobness values than that of suspicious lesions. Therefore, the mean and the maximum blobness values of a tumor candidate were used to eliminate False Positives.

$$\text{Blobness}_{\text{mean}}(\text{T}) = \frac{\sum_{p \, \epsilon \, T} Blobness(\lambda_{p})}{N_T}$$

$$\text{Blobness}_{\text{max}}(\text{T}) = \max_{p \, \epsilon \, T} Blobness(\lambda_p)$$

Where T indicates tumor candidate, N_T is total voxel, p indicate voxel belongs to tumor candidate, λ_p indicates Eigen value at the position p.

Blobness, morphology & internal echo were the three feature which helps to cancel false positives (FP) from tumor candidate. In ABUS blob structure are darker than surrounding tissue so using mean, max and standard deviation of the blobness values helps to extract blobness feature of the voxel. Internal echo feature were extracted using the mean, standard deviation, skewness and kurtosis of the intensity distribution. A morphology and shape feature provides useful information for tumor diagnosis. These features were adopted to discriminate tumors from non tumors. The morphology features includes shape and ellipse fitting. Shape features include the volume, radius, speculation, and two, 3-D compactness. The margin property of a lesion can be described by radius and speculation, and the two 3-D compactness features characterises the relation between surface and volume of a lesion. Degree of regularity of a tumor candidate can be described by the ellipse fitting features. A logistic regression model was applied to classify the tumors and the non tumors using the three features and estimate the tumor likeliness of the remaining tumor contender.

Two evaluation procedures were performed, they are 10 fold cross validation (10F-CV) and leave-One-Out cross validation (LOO-CV). In the 10F-CV, normal and malignant cases were portioned into 10 groups of equal in size. In the 10F-CV, the sensitivity was 100%, with 17.33 FPs per pass. The CADe system's sensitivity decreased to 90% and 70%, with 8.80 and 2.67 FPs per pass, respectively. In the LOO-CV, the sensitivity was 100%, with 17.45 FPs per pass. The CADe system's sensitivity decreased to 90% and 70%, with 10.23 and 2.67 FPs per pass, respectively. This CADe system gives more false positives and it takes more time to execute because of 200 3D images from ABUS.
Surgeon may remove healthy tissue surrounding tumor as a safer side to avoid cancer tissue which spreads around tumor. This area is called surgical margin. Main problem for surgeon is to deciding surgical margin. To the end, **Arturo Pardo et al.,** [24] proposed directional

kernel density estimator in hyperspectral images of samples were obtained using microsampling reflectance spectroscopy. Spectral normal variate (SNV) was used to remove multiplicative variations in reflectance due to differences in sample particle size, path length, substance concentration and/or thickness. SNV was found with the expression

$$g_k = \frac{r_k - \mu_k}{\sigma_k}$$

Here μ_k and σ_k were the sample average reflectance and sample standard deviation of the reflectance vector elements. This transformation allowed the expression of every spectrum r_k as reflectance variations of a pixel with respect to its average reflectance, in standard deviation units. Image as a vector in high dimensional space has to be dimensionally reduced data per pixel for further calculation using singular value decomposition matrix.

Vector normalization was proposed to get directional information in lower dimensional space. This can be achieved by dividing every vector by its normalised value of every spectrum as $x_k = \frac{a_k}{\|a_k\|}$. To differentiate healthy tissue (H_0) and Malignant tissue (H_1) technique was suggested from directional sampled spectrum directional kernel density estimation. The values of the estimated directional PDF at every pixel using d-KDE and the classification categories have been assigned. Since the value shown on the screen to the surgeon as either alpha channel overlay applied over the image or a multispectral colour of the image according to the results.

Estimation of directional PDF as $f_h(x|H_K) = \frac{c_{h,L}(K)}{n} \sum_{i=1}^{n} K\left(\frac{1-x^T x_{i,k}}{h^2}\right)$

Where K( ) is directional kernel to estimate PDF, c is normalized bandwidth.

$K(r) = e^{-r}$ is von Mises kernel function.

Maximum likelihood classification classifies each spectrum / pixel depending on its PDF value. A total of seven categories were created in order to quantify the classification. Malignant tissues are broadly classified as invasive lobular carcinoma (ILC), Invasive ductal carcinoma (IDC) and ductal carcinoma in situ (DCIS). Non malignant tissue types are Normal, Benign, Inflammation and Adipose.

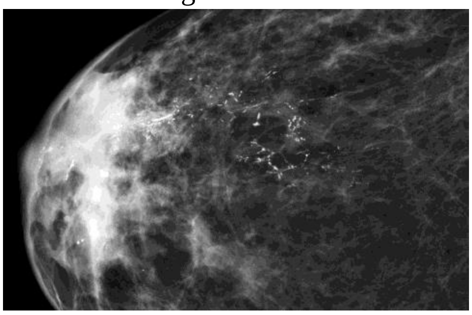
Surgical margin evaluations of extracted tumor can be implemented by d-KDE on hyperspectral images before closing intra operative cavity. And it gives sensitivity of 98% and specificity of 97%. It necessary to have more slices per sample and perform d-KDE for each slice instead of whole sample of tissue. And more research is required to assess the capability of multi slice d-KDE methodology.

B. Methods for detection of Microcalcification (MC) in Mammogram

Microcalcification is a very small calcium deposit of size as small as 1mm. and can be of single pixel representation in mammogram. Most of the mammogram has MC and extensive research progress to detect MC's. Threshold segmentation method largely depends on intensity value of the tissue which cannot be identified easily in stage 1 and stage 2 cancer. **Seokmin han et al.,** [25] proposed Dual energy mammography for tissue cancellation to identify in early stage. Anatomical noise can be reduced by threshold segmentation technique. Dual energy mammograms such as low and high energy x-ray images can also be used to reduce anatomical noise and to enhance the contrast of cancer lesions by calibrating with customized phantom. Adipose and glandular tissues are normal breast tissue which is compressed for predefined size. Such material is defined as phantom. Holes were drilled in such slab and filled with carcinoma tissue as least as 2 cm which correlates stage 1.

Mammogram with Microcalcification [radiopaedia.org]

Fig. 3.



Each object of interest is imaged with low and high energy x-rays and for calibration same performed for phantom which is a reference. Pixel pair both images of objects is compared with phantom. Each pixel value of object is mapped as two curves for both energies in phantom. Interaction of both energy curves defines mapping of the material in the phantom. If it is not interacting then material is different from phantom material. Contrast to noise ratio of region of interest is ratio of difference in intensity level of lesion region and background region to standard deviation of the value measured. High CNR value of 4.15 is measured for phantom of 1cm stage 1 lesion in 5 cm thickness phantom. Lesion identification can be improved by compensating Compton scattering and heel effect in the edge of the breast.

False positive due to incorrect judgement by oncologist and radiologist, can be overcome by SVM with FCM techniques proposed by **Gul shaira banu et al.,** [26] Mammography images taken from DDSM with 100 healthy images and 100 malignant images with masses and micro calcification. Digital mammography is converted to one dimensional data set. 1D wavelet transform was implemented on data set to produce independent wavelet coefficient corresponds to wavelet basis. To reduce background noise lower wavelet coefficients were removed.

Normal and malignant mammographic images can be classified by fixing a threshold. Mean value of coefficient of normal and malignant images is calculated. Lower quartile Q_1 is calculated by integral of probability density function for 25 % of the normal data. Upper quartile Q_3 is calculated by integral of probability density function for 75 % from lower value. The inter quartile range (IQR) is difference of Q_3 and Q_1. Average 1 can be identified as mean of normal + Q_1 and Average 2 can be identified as mean of malignant + Q_3. Then threshold is average of average 1 and average 2. Fuzzy C-means and support vector machine were implemented to predict normal or cancerous image using threshold valve.

Fuzzy clustering method allows one data belongs to different clusters by reducing the objective function by least squared error point. It is carried out for much iteration and converges to minimum point either in normal cluster or malignant cluster. Hyper plane is defined with maximising the distance vector from data set. Support vectors are training data set near to hyper plane. Data sets are classified by these SVM as normal and malignant. CWT with FCM gives 43 % of true positive and CWT with SVM gives 100 % of true positive.

Radiologist takes more time and it is complicated to classify microcalcification (which is smaller in size that occupies less pixel) as benign or cancerous tumor. To the end, **Zhili chen et al.,** [27] proposed topological modelling for classification of MCC. Topology of microcalcification cluster (MCC) gives topological feature space. This feature space helps to model microcalcification and classified by k-Nearest neighbors. Microcalcification cluster can be generated using morphological dilation based on shape of the structure, usually disk. Microcalcification of larger number which is located nearer gives malignant cluster whereas lesser number which is spread out is benign cluster. Microcalcification graph is created by connecting clusters. Microcalcification graph gives topological feature by capturing topological property. Benign and malignant clusters can be classified from topological feature space. By Euclidean weighted approach k-NN classifier is implemented for classification.

Classification Accuracy of 90% and ROC curve of 0.93 for LOOCV from MIAS data. Classification Accuracy of 96% and ROC curve of 0.94 for LOOCV from digital data. Classification Accuracy of 83.9 with tolerance of 6.3% and ROC curve of 0.9 for 10 -fold from DDSM. Classification is not reliable for structure less microcalcification cluster. Sparse distributed microcalcification is classified under benign.

Identification of microcalcification with various tissues at early stage is difficult for a radiologist. To this end, **Daniel Ruiz-Fernandez et al.**,[28] proposed segmentation of microcalcification surrounded by tissues can be detection by discrete wavelet packet transform (DWPT) and mathematical morphology. Mini-MIAS database image with microcalcification having dense glandular tissue, fatty tissue and fatty glandular tissue were reduced to 1024 pixel square matrix for uniformity. Background details occupy half of the image that can be eliminated by selecting region of interest (ROI). DWPT is implemented on ROI with filters H and G. From mother wavelet H wavelet filter is derived and G is a filter which scales the input. Mother wavelet such as Haar, Symlets, Coiflets and Daubechies were decided from the characteristics of input data as symmetry, vanishing moments, regularity and orthogonality.

Two dimensional DWPT with filters G and H gives four sub band images with low-low components which gives approximation that is low frequency details, low-high components which gives horizontal details, high-low components which gives vertical details and high-high components which gives diagonal details. Major information exists in approximation detail component which can be selected for morphological operation. Gray scale image of 256 gray levels can be represented by 8 bit data. In bitplane coding technique, most insignificant three bit has noise which can be eliminated by equating to zero. Sharpness of the boundary and edge details can be improved by unsharp masking. Image which is filtered with low frequency details is scaled by multiplying with weight factor and subtracting from original image. Microcalcifications are disk shaped structure which can be extracted by top hat transform. In this transform radius of the disk can be modified according to the requirement.

100% accuracy was achieved for fatty tissue with symlet wavelet having structuring element threshold value 9. Mother wavelet can be chosen according to the tissue type such as symlet for fatty tissue, Daubechies for dense glandular tissue and coiflets for fatty glandular tissue to give best results.

It is hard to detect Microcalcifications, because they appear small in diameter as 0.1mm which gives high local luminance with less contrast in mammogram. **Akshay S Bharadwaj et al.,** [29] proposed early detection algorithm where region of interest in mammogram is selected and reduced to 128 X 128 pixels for fast processing. Segmentation of breast region and background is done by Fuzzy c mean (FCM). All data point are clustered in five level c=5 and level of cluster fuzziness with m = 2. Least level is unwanted background and level four and five has necessary details which is further segmented b top-hat transform. This transform detects low intensity area and eliminates low contrast and high intensity area. Threshold based histogram separation gives ROI and isolated by watershed segmentation. Gibbs random field (GRF) which is combination of markov random field and Gibbs distribution detects pattern of MCs. Pixel value of MCs are higher and background has lower gray level, this pixels can be linked as a pattern called Cliques. Average intensity value of the cliques is compared with average value of normal neighbour window of 5x5 sizes to detect MCs. Single pixel cliques value can be compared with average of 3x3 neighbour windows and threshold value to detect single pixel MC.

Detection rate of 94.4% is achieved, with sensitivity of 93.7%. MC of smaller size can be detected and this algorithm is independent of size and orientation of the image.

False positive cases for microcalcification cluster are more due to dense breast tissue. So, early identification is not an easy task. To overcome this, **Wissam J baddar et al.,** [30] proposed sparse dictionary representation to enhance MC. Patch of breast tissue from various non cancerous mammograms is formulated as a dictionary called sparse representation (SR). Identifying difference between tissue patch of test image and estimated image can be used to remove background noise. Mammograms from DDSM with microcalcification are employed. Gray level mean value is identified and threshold value is fixed to remove surrounding tissue from MCs. Contrast enhancement is done by squared function intensity remapping. Patch size of 50x50 pixel is selected which is slightly larger than largest microcalcification.

Patch of breast tissue from various non cancerous mammograms is formulated as a dictionary called sparse representation (SR). Patch of tissue region is takeout from test image and represented as vector form. It is overlapped with sparse dictionary and sparse coefficient vector is formed. Original image and test image gives difference in sparse coefficient as error which can be used to locate MC location. Global adaptive thresholding technique was implemented to detect MCC. Statistical texture analysis gives spatial gray level dependence matrix (**SGLD**) features and LAW texture gives average gray level, spot and edges. Support vector machine (SVM) classifier is used to classify MCC from non malignant tissue.

SR based approach gives higher sensitivity of 97.3 % when compared to wavelet based sensitivity of 94%. Sparse representation approach gives better performance and it reduces false positives when compared to wavelet based decomposition approach.

Detection of microcalcification varies from one mammogram to other mammogram due to imaging artifacts, structure of milk duct and noise which resembles Microcalcification. To this end, **Maria V Sainz de cea et al.,** [31] proposed case adaptive method. Detection of microcalcification varies from one mammogram to other mammogram due to imaging artifacts, structure of milk duct and noise which resembles Microcalcification. Microcalcification detection is employed by detection function where threshold is fixed based on image set. There is a trade off between level of false positive and detection sensitivity. To detect MC more accurately, decision threshold can be varied that results in more false positive. So threshold must be a function that must be adaptive to image. Bayes risk model is designed with decision rule based on probability distribution of MC and probability distribution of FP. This allows developing a decision rule that is adapted to the noise characteristics of each case. 2-fold cross validation is performed for evaluation of MC through FROC curve, free response operating characteristics graph which is average fraction of true positive detection with false positive detection over a range of threshold value. SVM classification is used for MC classification.

For a 85% true positive bayes risk approach give 43% of false positive when compared to 62% in standard non adaptive method. Bayes risk approach is case adaptive MC detection in mammogram which reduces false positive in the detection. Above technique can also be implemented for true positive probability model.

Microcalcification appears as tiny spot in mammogram, due to high frequency image noise detectability of MC is hampered. This results in increase of false positive. To reduce FP rate, **Alessandro Bria et al.,** [32] proposed Adaptive variance stabilization transform based detection algorithm. Mammogram has image noise due to intensity dependent quantum noise that is created by the random distribution of the photons within the mammogram. This can be modelled by Poisson distribution. Implementing adaptive variance stabilizing transform (aVST) in pre-processing stage can remove the noise. Mammogram has image noise due to intensity dependent quantum noise that is created by the random distribution of the photons within the mammogram. This can be modelled by Poisson distribution. Implementing variance stabilizing transform (VST) in pre-processing stage can remove the noise. This gives dissimilar noise level for different mammogram which can be overcome by adaptive VST. Adaptiveness can be achieved by estimating noise level in each case.

Inner peripheral zone is discarded, low pass (Gaussian) filter is convolved with image to get smoothened image. On subtracting smoothed image from original image, signal can be separated from noise. Smoothed image is divided into bins based on gray scale. Each bins has weighted mean intensity$\hat{Z}$. Local contrast can be obtained as $L = \hat{Z} - Z$. Where, Z is individual intensity value of smoothed image.

Local contrast distributions were obtained. Noise level can be estimated by fixing a threshold value which 20% below maximum value obtained through Gaussian least square fitting. Adaptive variable can be estimated by computing least squares fitting of the samples of the noise to the square root noise model. Microcalcification detection was implemented with four classification tools such as ranking based cascade classifier, convolution neural network, support vector machine and weighted difference of Gaussian classifier.

FROC graph was plotted between true positive detection rate and false positive detection rate. Average mean sensitivity was improved by 0.81% for cascade, 0.82% for CNN, 4.52% for SVM and 1.6% for DoG classifiers implemented for pre-processed image with adaptive variance stabilized transform (aVST). MC detection with aVST is statistically better than fixed VST. SVM classifier gives best result because it is more sensitive to variation in noise data.

Table 1 Listing of popular algorithm to detect Microcalcification

Author	Algorithm used	Result
Seokmin Han et al.,[25]	Calibrated Phantom	Best Figure of merit (FOM) upto 5.5
Gul shaira banu et al., [26]	Continuous wavelet transform with SVM classifier	TP upto 100%
Zhili chen et al., [27]	Topological feature with k-NN classifier	Accuracy upto 96%
Daniel Ruiz-Fernandez et al.,[28]	Discrete wavelet packet transform with various wavelet	Accuracy upto 100% for symlet wavelet
Akshay S Bharadwaj et al., [29]	Combination of Gibbs distribution and Markov random field	Sensitivity upto 93.7%
Wissam J baddar et al., [30]	Sparse representation with SVM classifier	Sensitivity upto 97.3%
Maria V Sainz de cea et al., [31]	Bayes risk model based on probability distribution with SVM classifier	TP upto 85%
Alessandro Bria et al., [32]	Adaptive variance stabilizing transform with cascade, CNN, SVM and DoG classifier	Sensitivity is improved by 4.52% in FROC graph

C. Methods for detection of Architectural disorder in Mammogram

Architectural disorder is defined in Breast Imaging Reporting and Data System (BI-RADS). Without any detected mass, architectural distortion can be seen in normal breast. Anomaly identification by highly supervised support vector machine (SVM) technique using hyper plane fixing cannot detect texture of tissue which varies before masses and microcalcification appears that is early stages of cancer. To this end, **Gwenole quellec et al,** [33] proposed multiple-instance learning (MIL) algorithm. Microcalcification and masses can be detected by extracting features and classified as normal and malignant mammogram by weekly supervised multiple – instance learning method. It has been experimented on DDSM dataset to detect anomaly in mammographic images. Mammograms are portioned into small rectangular patch to apply MIL algorithm. This technique does not hold good for microcalcification because of small patches. Image is smoothened by median and derivative filter to avoid enhancement of noise. Breast edges can be segmented by fixing threshold on intensity value of the image and nipple can be identified by intersecting region of main ridge identified by Maurer distance transform with breast edge. Mass in mammogram can extracted my constructing contours of dense quasi concentric pattern by topographic approach.

Microcalcification is tiny calcium deposit which can be extracted by Fast Radial Symmetry Transform (FRST) that works out for high radial symmetric objects. Feature vector can be described as complementary of cumulative distribution function over lesion probability.

Region of Interest is defined as BAG and it is bifurcated into many instances. Feature vector of each instance of a bag is negative then image is negative for disease. If any one instance is positive then image is positive for disease. First local anomaly index is fixed and based on the result global anomaly index can be defined. These algorithms were proposed by five techniques such as diverse density, axis parallel rectangles, mi-SVM, MI-SVM and MIL boost. MIL classifier implemented by all five methods which week supervised technique gives best result compared to strong supervised SVM technique

Percentage mammographic density (PMD) is ratio of density to total breast area which used for risk scoring; PMD is not suited for large case studies due to large processing time. Mammographic texture scoring is even difficult because, extracting texture from mammogram is complicated. To overcome this, **Michiel kallenberg et al.,** [34] proposed unsupervised risk scoring method. Risk scoring in mammography can be automated by extracting artifice features. Breast tissue density is segmented and scoring the mammography by texture feature. Patient with increased mammographic density has high risk of carcinoma. Convolutional sparse auto-encoder is employed with four layers such as convolutional layer, pooling layer followed by two more convolutional layer of training set of weighted coefficient to learn the feature in an unsupervised method.

Breast tissue is segmented as background and pictorial muscle, fatty breast tissue and dense breast tissue in MD scoring. In MT scoring breast tissue are classified as control and malignant. Three datasets are density dataset with 493 images, texture dataset with 668 images and Dutch dataset with 394 images with mediolateral oblique (MLO) and craniocaudal (CC) with 95 % accuracy of automated result with radiologist conclusion.

D. Methods for detection of bilateral asymmetry in Mammogram

Breast cancer can also be diagnosed by asymmetry between both breasts in the mammogram. Asymmetry can be defined by existence of mass, ducts and dense tissue of one breast compared to other breast. **Paola Casti et al.,** [35] proposed analysis of structural similarity. DDSM and mini-MIAS mammograms with MLO and CC view with asymmetric cases were selected. Image resolutions were unified because they are from different data base. Pectoral muscle which is chest muscle in MLO view, Nipple and breast skin layer are anatomical structures which is common in all mammogram can be identified by Gabor filtering, gradient vector analysis, directionality and shape based constraints. Interpretation of mammogram by bilateral masking procedure were implemented as follows,

In first masking, eight equally spaced horizontal segments strips from top most pixels to bottom most pixels were created in CC view mammogram and eight equally spaced annular segments strips from nipple to pectoral muscle were created in MLO view mammogram.

In second masking, eight equally spaced vertical segments strips from nipple to chest wall were created in CC view mammogram and eight equally spaced perpendicular segments strips from nipple to pectoral muscle were created in MLO view mammogram. Segmented strip from one mammogram either left or right is flipped to other mammogram so that each segment can be matched for feature extraction. In a region of interest, structural variation can be obtained by variogram. Variogram is a descriptor which gives special dependency of the pixel value with respect to distance. Semivariogram can be defined as

$$\gamma(h) = \frac{1}{2N(h)}\sum_{m=1}^{N(h)}[f(u_{m,0}) - f(u_{m,h})]^{2}$$

Where N(h) is pair of pixel separated by a distance h, u are the spatial coordinate vectors with lag distance h, f is value of the gray level. Mass in mammogram can be detected using cross variogram function between the pair of pixel values. From spherical Semivariogram descriptor, parameters like nugget, sill, range and geometric anisotropy direction analyser were calculated. And absolute difference between these four parameter derived from one side of mammogram is compared with other side of the mammogram. Higher these values define lower the similarity which results in asymmetric case.

Structural similarity can be identified by correlation based structural similarity index method (CB-SSIM) by calculating mean intensity and contrast of the image. To avoid spatial distortion complex wavelet structural similarity (CW-SSIM) can be implemented which is independent of space and image distortion. Features extracted from bilateral region can be classified with receiver operating characteristics (ROC) curve without classifier. For better sensitivity classifier like Bayesian classifier, ANN-RBF artificial neural network with radial basis function were used individually in CC and MLO view. Best ROC curve A_z value 0.93 for ANN-RBF, 100 % sensitivity, 88% specificity and 94 % accuracy. Combination of land marking, automatic masking, Gabor filter, and semi-variogram gives best result in finding bilateral structural asymmetric of breast cancer.

Maxine Tan et al., [36] proposed algorithm for near term cancer development. Prediction of breast cancer development can be obtained by comparing current image with three prior images. Four sequential full field digital mammography FFDM images were computed for similarities in structure, density and texture features.

Mammographic images were assessed for tissue pattern and categorised to four subgroups such as 1) identifying similarity in structure, (SSIM) **S**tructural **sim**ilarity method compares for local pattern of values of pixel intensities which was normalised for contrast and luminance between right and left, bilateral symmetry of breast image. CB-SSIM is correlation based indexing it is 2D cross correlation between left and right breast region. SSIM gives errors in scale and geometric disorder which can be surmount by CW-SSIM, complex wavelet estimates similarities in transformed domain. These structural similarity methods detect dense breast pixel value which is more than mean value of the breast. 2) Weber local descriptor, WLD is gradient orientation of pixel value which is ratio of intensity difference of the pixel with its neighbour and real intensity of the pixel. Local salient pattern was extracted for comparison. 3) RLS: run length statistics & features derived on GLCM: Gray level co-occurrence matrix, gray level RLS gives features which have good differentiating power among the prior images. Tissue character feature can be identified by GLCM method which relates homogeneity, energy and contrast between images. 4) Features based on gray level magnitude such as mean, skewness, entropy, standard deviation and kurtosis were calculated and related between the images.

Features extracted from left and right of MLO and CC view mammographic images can be subtracted from prior image to give asymmetric feature. Support vector machine (SVM) was built with leave one case out (LOCO) based validation to train and investigate risk prediction. SVM based model gives accuracy of 65.7%, sensitivity of 46.5% and specificity of 83%. Risk model gives 71.2% positive prediction and 63.2% negative prediction. Successful implementation with higher accuracy of prior FFDM screening examination can give good impact pre-stage breast cancer prediction.

V. DISCUSSION

Breast cancer detection can be improved further by increasing performance of the CAD systems. Still radiologist doesn't depend fully on CAD result because of false positive rate. In recent years, early detection of cancer was identified by detecting MC. Mass detection is a critical task when compared to MC because of similarity between features of mass and normal breast benign. Not much research has been proposed in bilateral asymmetry of breast. Considering mammography, digital is dominating conventional film mammogram in recent years.

VI. CONCLUSION

Detection of breast cancer from cancer by mammogram was started well before 1970's [6]. In past two decades significant work on CAD reduced work pressure on radiologist. This survey paper provides brief idea about detection of malignancy in mammogram. Still much improvement is required in implementing algorithm for breast cancer detection.

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